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Automated diagnosis of Lungs Tumor Using Segmentation Techniques

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Abstract— The Objective is to detect the cancerous lung nodules from 3D CT chest image and classify the lung disease and its severity. Although so many researches has been done in this stream, the problem still remains a challenging one. To extract the lung region FCM segmentation is used. Here we used six feature extraction techniques such as bag of visual words based on the histogram oriented gradients, the wavelet transform based features, the local binary pattern, SIFT and Zernike moment . The Particle swarm optimization algorithm is used to select the best features.

Keywords— ***Lungs CT, image segmentation, PSO, SVM, ELM, k-NN, NB.***

I. INTRODUCTION

Due to increasing rate of smoking and air pollution lung cancer is main cause for deaths in different countries. CT is the best modality to diagnose the lung disease. Time and cost are the two important factors. The early detection of lung nodule growth cure the disease of the patient. According to staging of lung cancer the severity will be found. The radiologist will help the diagnosis efficiency by calculating the number of nodule growth in stages X rays image is not sufficient for early detection of lung cancer [2], [4]. CT plays an important role on cancer staging evaluation. It is challenging task due to low contrast, size and location variation in CT imaging. Distinguishing the cancerous nodules from the blood vessel is the challenging task because in the central lung regions lung nodules are confused with the blood vessels imaged in cross section. The detection of lung nodule have been found such as feature base, template matching based and neural based. In [5] the organs of interest and lung area was classified in to two clusters, air cluster and other organs cluster. Using Gaussian distribution as reference images, template
matching algorithm is used to detect the nodules in chest CT images. Tuo Xu et al.[1] proposed an automatic global edge and
region force (ERF) field guided method for lung field segmentation. Experimental results demonstrated that the proposed method is time efficient and improves the accuracy, sensitivity, specificity and robustness of the segmentation results. In the lungs accurate lung segmentation allows the detection and quantification of abnormalities. A automatic method for segmentation of the lungs and lobes from thorox CT scans by Van Rikrort et al. [7]. Here region growing approach is used to segment the region and morphological operations are done. Multiatlas segmentation will be applied to the results. Sobel edge [9] detection method is used to segment the CT lung image. Jun lai et al.[8] used a fully automatic segmentation for pulmonary vessals in plain thoraic CT images.

Vessal tree reconstruction algorithm [10] reduced the number of false positives by 38%. Camarlinght et al.[11] has used three
different computer aided detection techniques to identify the pulmonary nodules in CT images.

Abdulla & Shaharun [12] used feed forward neural networks to classify lung nodules in X-ray images and with smaller feature of area, size and perimeter. Kuruvilla et al.[13] have used six distint parameters including skewness and fifth and sixth central moments extracted from segmented single slices and used feed forward back propagation neural network with them to evaluate accuracy . In Riccardi et al[16] the authors presented a new algorithm to automatically detect nodules with 71% overall accuracy using 3D radical transforms . In neuro imaging data of brain using deep Boltzmann machine for AD/MDC diagnosis is done by the author Suk et al. [17]. The method achieves a excellent diagnostic accuracy of 95.52%.To the best of our knowledge there has been no work that uses deep features from lung nodule classification.

In this paper the trainned image was preprocessed then the lung region will be extracted using FCM segmentation. After that we found the lung cancer detection by extracting the features.

Cancerous lung nodules detection from CT chest image

The block diagram of the proposed method is shown in fig.1. To detect the location of the cancerous lung nodules this paper uses a novel algorithm. First we denoised the input image by wiener filter. Contrast is enhanced by histogram equalization. To extract the lung region the FCM segmentation is used. The further details of these are discussed below:

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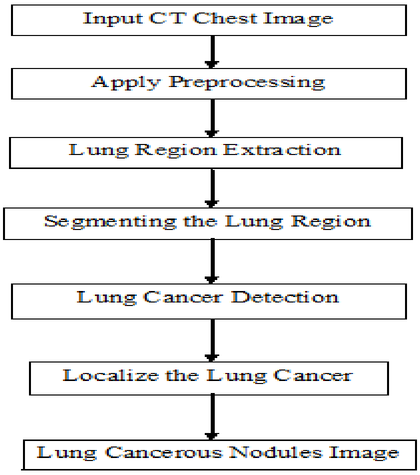

Fig.1 Cancerous lung nodule detection

A. GETTING THE ORIGINAL IMAGE

In this module, this paper get the original image for the segmentation of the lung from the CT image.

B. PREPROCESSING

In an easy way making the image ready for the processing is known as Preprocessing. Preprocessing is an improvement of the image data that suppresses unwanted degraded pixels important for futher processing.

I. Apply Denoising using Wiener Filter

In signal processing, the Wiener filter is a filter used to produce an estimate of a desired or target random process by linear time-invariant filtering an observed noisy process, assuming known stationary signal and noise spectra, and additive noise. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach, and a more statistical account of the theory is given in the MMSE estimator article. Typical filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

1. Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
2. Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)
3. Performance criterion: minimum mean-square error (MMSE)

II. Apply Contrast Enhancement

Digital image processing is still new enough for most people that no matter how much this paper read, experiment and work at it, there seems to be an endless amount to learn. This is particularly true as regards photoshop that invaluable tool yet also bottomless pit of a time sink. But every now and then a little tidbit comes along that moves ones work either easier or better, and this one, which I call Contrast Enhancement – is one of the best that I have seen in a while. The `imadjust` increases the contrast of the image by mapping the values of the input intensity image to new values such that, by default, 1% of the data is saturated at low and high intensities of the input data.

C. LUNG REGION EXTRACTION

I. Apply FCM Segmentation

In fuzzy clustering, every point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely too just one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of cluster. An overview and comparison of different fuzzy clustering algorithms is available. Any point x has a set of coefficients giving the degree of being in the kth cluster $w_k(x)$. With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster:

$$c_k = \frac{\sum_x w_k(x)^m x}{\sum_x w_k(x)^m}.$$

The degree of belonging, $w_k(x)$, is related inversely to the distance from x to the cluster center as calculated on the previous pass. It also depends on a parameter m that controls how much weight is given to the closest center. The fuzzy c-means algorithm is very similar to the k-means algorithm:

- Choose number of clusters.
- Assign randomly to each point coefficients for being in the clusters.
- Repeat until the algorithm has converged (that is, the coefficients change between two iterations is no more than ε, the given sensitivity threshold) :
  - a)Compute the centroid for each cluster, using the formula above.
  - b)For each point, compute its coefficients of being in the clusters, using the formula above.

II. Extraction of Lung Region

In this technique, the lung region is obtained by the extraction method. The input is from the segmented region and it extracts the lung region and gives the output image.

D. SEGMENTING THE LUNG REGION

I. Applying Filling Holes

In this method, after extracting the lung region the holes in the lung region are filled by the segmentation techniques.

E. LUNG CANCER DETECTION

I. Extract Features

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately.

Usually, one of the main problems in analyzing complex data is the large number of variables involved in the data. A lot of memory and computation power is necessary to analyze the data . But feature extraction method can be used to construction of variable combinations to overcome these obstacles but it still describes data accurately. So achievement of best result happens. when an expert constructs a set of application-dependent features.

II. Detect the Lung Cancer

After the extraction of the features from the image, by using the features the cancer in the lungs was identified.

F. LOCALIZE THE LUNG CANCER

In computer vision and image processing, this paper often perform different processing on “objects” than on “texture.” In order to do this, this paper must have a way of localizing textured regions of an image. For this purpose, this paper suggest a working definition of texture: Statistics describes the term “texture” more accurately when compared to describing the configuration of all the parts. Texture is a part of local statistics. But Outliers do not seen to be local statistics and draw our attention. This definition suggests that to find texture this paper first extract certain basic features and compute their local statistics. Then this paper compute a measure of saliency, or degree to which each portion of the image seems to be an outlier to the local feature distribution, and label as texture the regions with low saliency. This paper present a method, based upon this idea, for labeling points in cancer images as belonging to texture regions. This method is based upon recent psychophysics results on processing of texture.

I. Lung tissue classification and severity finding

The overall block diagram of the proposed method is shown in Fig. 3.1. After finding the location of the cancerous lung nodules the next process is to classify the lung disease name and its severity based on the feature extraction. Among several feature extraction methods this paper uses six feature extraction technique such as the bag of visual-words based on the histogram of oriented gradients, the wavelet transform-based features, the local binary pattern, SIFT, Zernike Moment. After extracting the features the Particle Swarm Optimization (PSO) algorithm is used for select the best features. Finally these features are classified by using the Extreme Learning Machine (ELM) method. To analyse the performance of the ELM method it is compared with the five commonly used classifiers including support vector machine (SVM), Bagging (Bag), Naive Bayes (NB), k-nearest neighbor (k-NN), Extreme Learning Machine (ELM) and AdaBoost (Ada).

II.Methods

The features are extracted from the Lungs CT dataset. This project extracts four types of ROI features, including the bag-of-visual-words based on the HOG (B-HOG), the wavelet features, the LBP, and the CVH. We have 18-D B-HOG features, 26-D wavelet features, 96-D LBP features, and 40-D CVH features. Total 180 features are extracted. The details of each type of features are given as follows.

I. B-HOG:

The HOG feature is a texture descriptor describing the distribution of image gradients in different orientations. Following the HOG feature extraction scheme of Dalal and Triggs, we divide a ROI into smaller rectangular blocks of 8 × 8 pixels and further divide each block into four cells of 4 × 4 pixels. An orientation histogram which contains nine bins covering a gradient orientation range of 0–180° is computed for each cell. Then, a block is represented by the linking of the orientation histograms of cells in it. This means a 36-D HOG feature vector is extracted for each block.

The commonly used image representation based on HOG features is to join the feature vectors of all the blocks in the image in sequence.All the HOG based images should have the same size. Because , in the absence of same sized image diverse resultant feature vector are obtained. But in CT lung images, the size of ROIs differ patient to patient and different lesions of the lungs. So the HOG based image has the obstacle which makes it non applicable in this study. To solve this problem, we adopt the bag-of-visual-words on HOG features as the ROI representation. However, different from the original bag-of-visual-words method, we use a clustering algorithm based on Gaussian mixture modeling (GMM), instead of the k-means algorithm, to generate more accurate visual words. In this paper, total 18 visual words are obtained.

The 36-D HOG feature vector of each block is mapped to the visual word corresponding to the highest likelihood for it. Then, the number of HOG feature vectors assigned to each visual word is accumulated and normalized by the number of all the HOG feature vectors to form a 18-D histogram representation of the ROI.

II. WAVELET FEATURES:

Wavelets are important and commonly used feature descriptors for texture analysis, due to their effectiveness in capturing localized spatial and frequency information and multiresolution characteristics. In this paper, the ROIs are decomposed to four levels by using 2-D symlets wavelet because the symlets wavelet has better symmetry than Daubechies wavelet and more suitable for image processing. Then, the horizontal, vertical, and diagonal detail coefficients are extracted from the wavelet decomposition structure. Finally, we get the wavelet features by calculating the mean and variance of these wavelet coefficients.

III. LBP FEATURES:

The LBP feature is a compact texture descriptor in which each comparison result between a center pixel and one of its surrounding neighbors is encoded as a bit. In this way, we can get an integer for each pixel. Then, the frequency of each integer is figured out on the ROI level to obtain the corresponding feature vector. The neighbourhood in the LBP operator can be defined very flexibly by using circular neighbourhoods and the bilateral interpolation of pixel values. These kinds of neighbourhoods can be denoted by (P, R), which means we evenly sample P neighbors on the circle of radius R around the center pixel. The corresponding LBP features will be denoted as LBP(P, R) in the following descriptions. We consider multiple P and R to get multiscale LBP features.

IV. CVH FEATURES:

CVH means the histogram of CT values. In lung CT images, the CT values of pixels are expressed in HU. We compute the histogram of CT values over each ROI. The number of bins in the histogram is determined by experiments. In fact, we obtain various CVHs with different numbers of bins. Each CVH is tested for classification under k-NN classifier, and the corresponding CAR is calculated. Then, the number of bins, which brings the highest CAR, is adopted. This choice will keep unchanged for all the experiments.

V. SIFT FEATURES:

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect . Set of related images are stored in a database is the keypoint of SIFT.Based on Euclidean distance of the image feature vectors an object is recognized in a new image to the data base. The new images are identified by location, scale, and orientation in filters. Here efficient Hash table is used and the consistent clusters is performed rapidly. Each cluster of 3 or more features accept on an object and verification is done. Subsequently outliers are discarded. Finally the probability that a particular set of features denotes the object and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.

VI. ZERNIKE MOMENT FEATURES:

1. The two-dimensional complex Zernike moments of a digital image with current pixel $P(x,y)$ are defined as:

$$Z_{nm} = \frac{n+1}{\pi} \sum_x \sum_y P(x,y) V^*_{nm}(x,y), \; x^2 + y^2 \le 1$$

2. The Zernike polynomials defined in polar coordinates as:

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho) \exp(jm\theta)$$

3. The real-valued radial polynomial of ρ given as follows:

$$R_{nm}(x,y) = \sum_{s=0}^{\frac{n-|m|}{2}} \frac{(-1)^s (n-s)! \, \rho^{n-2s}}{s! \left(\frac{n+|m|}{2} - s\right)! \left(\frac{n-|m|}{2} - s\right)!}$$

4. Zernike moments can then be expressed using central and normalized regular moments as

$$Z_{nm} = \frac{n+1}{\pi} \sum_{k=m}^{k_1} B_{nmk} \, \mu_{k-2j-m+j1,\, 2j+m-j1}$$

VII. FEATURE SELECTION USING PSO:

In order to achieve good classification results, we usually use several types of features at the same time. Since the different types of features may contain complementary information, it could bring better classification performance through selecting discriminative features from various feature spaces. This idea has attracted a lot of attention in the related fields, including the medical image classification. According to Guyon and Elisseff, the feature selection techniques can be organized into mainly three categories: Filter, Wrapper, and Embedded methods. We follow their taxonomy to review the feature selection methods for medical image classification.

For feature selection this project uses PSO. A bird which is seeking food communicates with its neighbouring birds to make it a multidimensional search. Similarly, PSO aims at giving a candidate solution to a problem. It is a method of meta heuristics because it does few or no assumption of the problem and can search much wider. But it does not guarantee a solution because gradient is not used to optimize the problem. This is also an advantage because gradient is needed for classical methods like quasi-neuton method and gradient descent method. Partially irregular, noisy and variable problems can be optimized ideally by PSO.

III.Testing Phase

In the testing phase the above mentioned feature extraction and feature selection are performed for the given input image. then apply the Classification to find the given input image's disease name.

I. SVM

SVMs (Support Vector Machines have associated learning algorithms and they can recognize patterns and analyze data and are supervised learning models. SVM algorithm makes a given set of training examples get assigned to one or the other category and it is a non probabilistic linear binary classifier.

II. Bag

The bag-of-words model is a simplifying representation used in natural language processing and information retrieval. In this model, a text (a sentence or a document) is represented as the bag (multiset) of its words , disregarding grammer and even word order but keeping multiplicity. Recently , the bag-of-words model is commonly used in methods of document classification, where the (frequency of) occurrence of each word is used as a feature for training a classifier.

III.NB

In machine learning Naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Baye’s theorem with strong (naïve) independence assumptions between the features. Naive Bayes classifiers are highly scalable requiring a number of parameters linear in the number variables (features/predictors) in a learning problem. Maximum likelihood training can be done by evaluating a closedform expression, which takes linear time.

IV. k-NN

k-NN algorithm is used for classification and regression in pattern recognition. Here the input consists of the k closeset training examples in the feature space. In k-NN classification , the output is a class membership. The k-NN decision making as equivalent to a Bayesian decision making procedure in which the number of neighbors of each type is used as an estimate of the relative posterior probabilities of class membership in the neighborhood of a sample to be classified. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k-nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

V. Adaboost

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AdaBoost, short for "Adaptive Boosting", is a machine learning meta-algorithm. This can be used in conjunction with many other types of learning algorithms. The output of weak learner which is combined in to a weighted sum. Adaboost is adptive in the sense that subsequent weak learners are tweaked in favour of those instances misclassified with previous classifiers.

VI. ELM:

A new learning algorithm called extreme learning machine (ELM) for single- hidden layer feedforward neural networks (SLFNs) which randomly chooses hidden nodes and analytically determines the output weights of SLFNs. This algorithm tends to provide good generalization performance at extremely fast learning speed.

The algorithm for ELM is explained below:

1. Randomly generate the hidden nodes as well as randomly assign the weights $W_{i,j}$ for $i = 1..m;\ j = 1..n$.
2. Activate the input image values $x_i, i = 1..n$ and calculate the net input to hidden layer using $$H_{i,j} = \sum_{i=1}^{n} x_i W_{i,j},\ j = 1..m$$.
3. To calculate the net output from the hidden to output layer repeat the step 2.

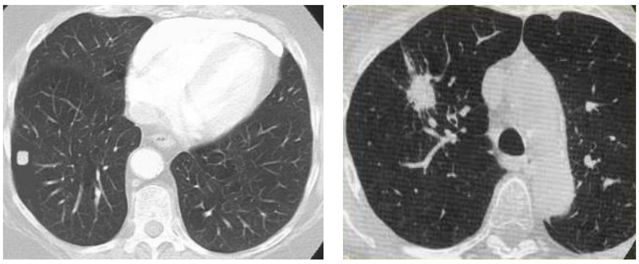
IV . Performance Analysis

A. Expiremental Images

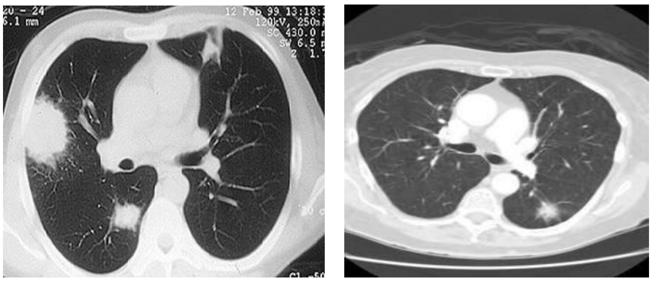
The instances of nine categories of CISLs were collected from the Cancer Institute and Hospital. The lung CT images were acquired by CT scanners of GE LightSpeed VCT 64 and Toshiba Aquilion 64 and saved in DICOM 3.0 format. The slice thickness is 5 mm, the image resolution is 512×512, and the in-plane pixel spacing ranges from 0.418 to 1 mm (mean: 0.664 mm). The sample images are shown in the below Fig.3.

B. Performance Analysis

To evaluate the performance of the proposed method several performance metrics are available. This paper uses the Precision Rate, Recall Rate, Classification Accuracy, Error Rate and F-Measure to analyses the performance.



(a) (b)



(c) (d)

Fig. 2. Expiremental Images

1. Precision Rate

The precision is the fraction of retrieved instances that are relevant to the find.

$$Precision = \frac{TP}{TP + FP}$$

where TP = True Positive (Equivalent with Hits)
FP = False Positive (Equivalent with False Alarm)

2. Recall Rate

The recall is the fraction of relevant instances that are retrieved according to the query.

$$Recall = \frac{TP}{TP + FN}$$

Where TP = True Positive (Equivalent with Hits)
FP = False Negative (Equivalent with Miss)

3. F-Measure

F-measure is the ratio of product of precision and recall to the sum of precision and recall. The f-measure can be calculated as,

$$F_m = (1 + \alpha) * \frac{Precision * Recall}{\alpha * (Precision * Recall)}$$

4. Classification Accuracy

Accuracy is the measurement system, which measure the degree of closeness of measurement between the original disease and the detected disease.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

Where, TP – True Positive (equivalent with hit)
FN – False Negative (equivalent with miss)
TN – True Negative (equivalent with correct rejection)
FP – False Positive (equivalent with false alarm)

5. Error Rate

Error Rate is the measurement system, which measure no of falsely identified diseases name form the given input CT scan images.

$$\text{Error Rate} = \frac{\text{No of Images of Falsely Identified D}}{\text{Total No of Images}}$$

To analysis the performance of the proposed system, it is compared with various techniques by using the performance metrics which are mentioned above. This is shown in the below tables and graphs. The performance comparison of the classification accuracy value of the proposed method and other four existing approaches such as Adaboost K-NN, NB and Bag is shown in the below Table.

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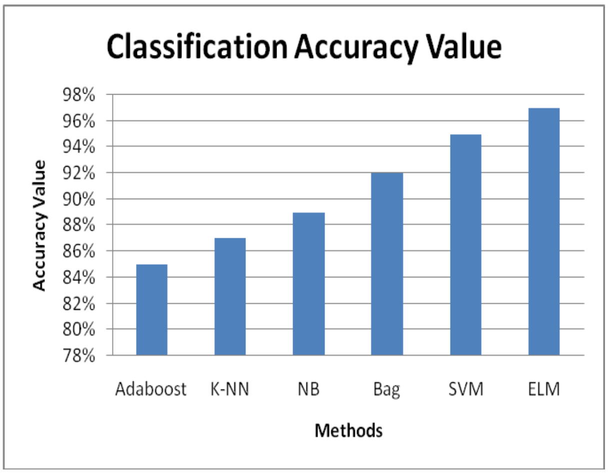
Methods	Classification Accuracy Value
Adaboost	85%
K-NN	87%
NB	89%
Bag	92%
SVM	95%
ELM	97%

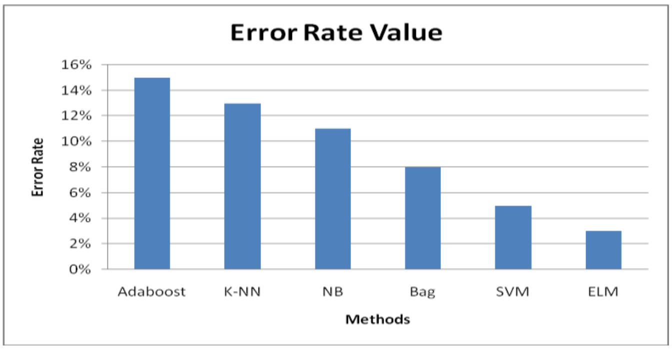
In the above Table.1 the classification accuracy value of the five methods including the proposed method is given and then it is compared. The classification accuracy value of the ELM method is higher than the other method.



The Classification Accuracy value of the proposed method is higher than the other four existing approaches. It is clearly shown in the above Fig.3. Because of the higher classification accuracy value, the ELM method is best than the other four existing approaches.

Methods	Error Rate Value
Adaboost	15%
K-NN	13%
NB	11%
Bag	8%
SVM	5%
ELM	3%

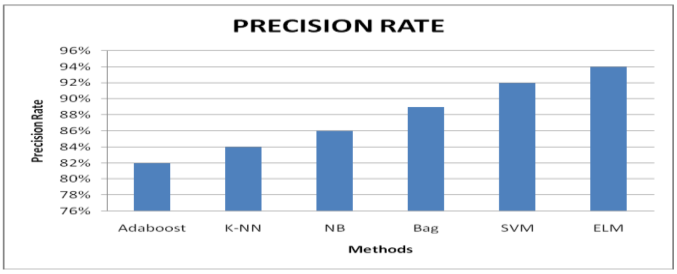
The performance comparison of the error rate value of the proposed method and other four existing approaches such as Adaboost K-NN, NB and Bag is shown in the below Fig.4.



The error rate value of the five methods including the proposed method is given and then it is compared. The error rate value of the ELM method is lower than the other method. The Error Rate value of the proposed method is less than the other four existing approaches. It is clearly shown in the above Fig.5. Because of the lower error rate the proposed method is best than the other four existing approaches.

Methods	Precision Rate
Adaboost	82%
k-NN	84%
NB	86%
Bag	89%
SVM	92%
ELM	94%

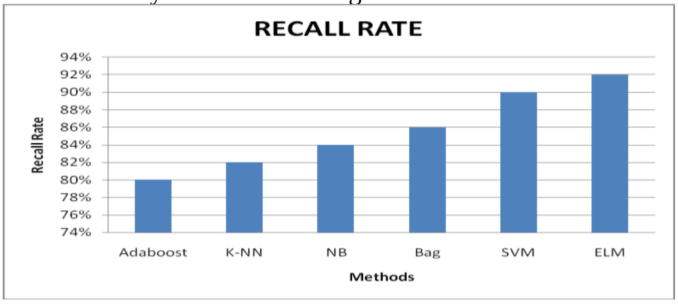
From the table it is shown that the precision rate value of the ELM method is higher than the other existing approaches. So the ELM method is best than the existing approaches. The graph of precision rate analysis is shown in Fig.5.



The performance comparison of the Recall Rate value of the proposed method and other four existing approaches such as Adaboost K-NN, NB and Bag is shown in the below Table.

Methods	Recall Rate
Adaboost	80%
K-NN	82%
NB	84%
Bag	86%
SVM	90%
ELM	92%

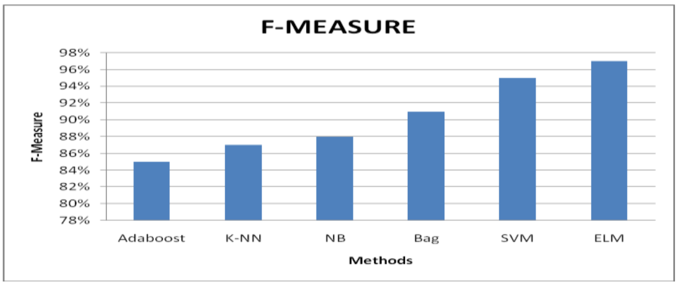
From the table it is shown that the recall rate value of the ELM method is higher than the other existing approaches. So the ELM method is best than the existing approaches. The graph of recall rate analysis is shown in Fig.4.16.



The performance comparison of the F-Measure value of the proposed method and other four existing approaches such as Adaboost K-NN, NB and Bag is shown in the below Table.1.

Methods	F-Measure
Adaboost	85%
K-NN	87%
NB	88%
Bag	91%
SVM	95%
ELM	97%

From the table it is shown that the F-Measure rate value of the ELM method is higher than the other existing approaches. So the ELM method is best than the existing approaches. The graph of precision rate analysis is shown in Fig.7.



The F-Measure value of the proposed method is less than the other four existing approaches. It is clearly shown in the above Fig.5. Because of the lower error rate the proposed method is best than the other four existing approaches.

V.CONCLUSION

This study measuring and investigating a new method for segmentation performance using FCM algorithm and after extracting the features the PSO is used to select the best features. This combination significantly improves the current state. To compare the performance , five criteria are used such as classification Accuracy , Error Rate , Precision Rate , Recall Rate and F measure. Experimental results show that the ELM performs better than the other classifiers.

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